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RESEARCH ARTICLE

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IMAGE QUALITY ASSESSMENT FOR FAKE BIOMETRIC DETECTION

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ABSTRACT

Image quality measures have been developed to predict the quality of the image. In this paper we have proposed the No reference (NR) and Full reference (FR) metric to assess the quality of the biometric images. In NR Image Quality Assessment (IQA) measure the quality of the test image is measured without any reference image. NR image quality is useful in measuring the quality of JPEG compressed image. FR IQA methods rely on the availability of a clean undistorted reference image to estimate the quality of the test sample. In this paper we have used Error Sensitivity Measures (MSE,PSNR,SNR,SC,MD,AD,NAE,RAMD,LMSE), Structural Similarity Measures (SSIM,MSSIM,WSSIM) and Information Theoretic Measures (VIF,RRED) to identify forged biometric images (Finger print and face). After measuring these values these are compared with the threshold values (Perfect quality image) which are stored in the database.

Keywords- Image Quality Assessment, No Reference, Full Reference, Biometric.

I.INTRODUCTION

The development of imaging and multimedia technology in various fields leads to the usage of the recorded images in so many areas. The images acquired may be distorted by so many factors which escort the necessary for assessing the quality of it. Quality analysis is a technical challenge because it is most helpful when the measures reflect the performance sensitivities of one or more target biometric matchers. In order to understand the quality assessment of the biometric images we need to inspect the artifacts that commonly affect the images. The quality of the biometric input depends on several facts like the acquisition device, environment, human interaction with the device and etc., The evaluation of quality of image may be divided into two classes, subjective and objective methods. Subject measure is purely experimental where some subjects (human) are invited to judge the quality of the image based on the protocol normalized by International Telecommunication Union (ITU) [1]. Subjective tests are eare costly and time consuming.The subjective testing process take a week or month thus becomes a bottleneck in the deveopment of the coder. Also In order to obtain accurate results large number of subjets are required.Subjective test data is accurate and valid for particular set of viewing conditions only for which the test is already performed. If new conditions arrives then we need to perform new tests[2].

Table 1. Mean opinion score

1	2	3	4	5
Very Poor Quality	Poor Quality	Good Quality	Very Good Quality	Excellent Quality

The objective method used to measure the quality of the image enumarate the error between the distorted image and the reference image. Objective image quality metric is clasified into three type based on the availability of reference image. No reference IQA approach refered as the automatic quality assessment technique which receives only the distorted image as the input andmeasure the quality of that image without any reference image [3][4]. Noreference IQA metric was developmed in 2004 [5] to produce a quality value form the fingerprint image that is directly predictive to expected matching performance. The most commonly used approach named full reference used a reference image and distorted image as input and will extract the features from the distorted image and compare it with the reference image featues in the database and will flaunt the distortion ratio. The third type called the reduced reference quality assessment metric uses the distortion image ad partial reference image as input which helps to evaluate the quality of distorted image. This paper focuses on Full reference and no reference image quality metrics. The paper is organized as follows Section II describes the related work of No Referenec and Full Reference metrics. Section III shows the Proposed work of this paper. Section IV presents the Results obtained and its discussion. Section V gives the details about the future work and Conclusion.

II.PREVIOUS WORK

Quality assessment (QA) of an image measures its degradation during acquisition, compression, transmission, processing, and reproduction. Several QA algorithms exist in image processing literature, which pursue different philosophies, performance, and applications. Objective blind or No-reference (NR) image quality assessment (IQA) is referred as the automatic quality assessment of an image using an algorithm such that the only information that the algorithm receives before it makes a prediction on quality is the distorted image whose quality is being assessed. NR-IQA algorithms follow one of three approaches: 1) **distortion specific approach** in which they used a distortion specific model to develop an objective algorithm which is used to predict the subjective score. 2) **Training based approach** – the quality of the image is predicted by training the model using the features extracted from the input image. 3) **Natural scene statistics (NSS) approach** – it specify that the natural images of the world occupy a subspace in the total subspace and seek to find the relation between the natural image and the tested input image. Many algorithms have been proposed in the NSS approach in which some is transform specific like NRIQA using DCT [7]. In this paper they have proposed an algorithm which is trained using features derived directly from a generalized parametric statistical model of natural image DCT coefficients against various perceptual levels (masking, cortical decompositions, motion perception) of image distortion. [8] – [12] measures the quality of the distorted image of type sharpness and blur and is based on pixel derivatives, kurtosis, DCT coefficients, spread of edges. Another NR IQA metric [13] uses the texture masking and luminance masking effects to measure the impact of ringing artifact. [14] proposed a training based general purpose NR IQA metric to measure the quality of the image. It extracts patch level features and explores information of training images for local descriptor encoding. This process requires less domain knowledge compared with previous approaches. Also instead of explicitly building a statistical model for image patches in high-dimensional feature space, in this paper they have used a visual codebook-based method for feature space quantization and then learns the mapping from the quantized feature space to image quality scores. A training based method which uses so many low level features to measure the image quality and these features are used in an algorithm to measure the relevant image measure. In such training based paradigms, the strength of the results heavily weighs on having a comprehensive set of discriminant features for the desired task.

The NR IQA NSS Approach proposed by [6] is based on the principal that the natural images statistical properties are been modified by some distortions. [6] Used a NR IQA model that is purely based on Spatial NSS mode which does not depend on the mapping of other domain like wavelet, DCT and etc., BRISQUE (Blind/Reference less Image Spatial QUality Evaluator) is a natural scene statistic (NSS)-based distortion-generic blind/no-reference (NR) image quality assessment (IQA) model which operates in the spatial domain. It does not compute distortion specific features such as ringing, blur or blocking, but instead uses scene statistics of locally normalized luminance coefficients to quantify possible losses of 'naturalness' in the image due to the presence of distortions, thereby leading to a holistic measure of quality. BRISQUE has very low computational complexity, making it well suited for real time applications. BRISQUE features may be used for distortion-identification as well. [16] Used the NSS features introduced in Blind/Referenceless Image Spatial QUality Evaluator (BRISQUE) to compute features over every image patch. They extract a quality-aware visual word which is based on NSS features on which the topic model is applied. The quality score is then measured by calculating the similarity ration between the probability of occurrence of the different topics in an unseen image and the distribution of latent topics averaged over a large number of pristine natural images. The visual words are formed by clustering features computed from multiple patches across all the images in the collection. Each image is divided into overlapping patches of size and local BRISQUE features are computed over each patch. Feature vectors from all patches across all images are clustered into W = 400 visual words using the - means clustering algorithm with the squared Euclidean distance metric.

III.IMPLEMENTATION

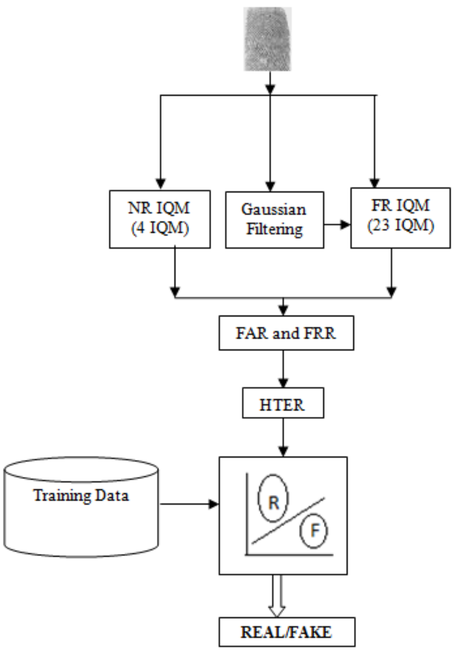

Fig 1. Diagram for Biometric Protection Method

The fake biometric detection system that basically having two classes: real or fake. In this present work, the novel parameterization to be implemented by using 27 Image Quality Measures. A general diagram of biometric protection method based on Image Quality Assessment in this present work shown in fig 1. Here, the input image is classified as real or fake. First, the feature vector has been generated for the input image based on that classified as the image is real (generated by a genuine trait) or fake (synthetically produced). Initially, it performs Full Reference Image Quality Metric and No Reference Image Quality Metric. FR that having two input: (i) the user input image and (ii) Gaussian noise applied to that input image. FR performs 23 Image Quality Measures (IQM). NR that having only one input image that is user input image. NR performs 4 Image Quality Measures (IQM). The final parameterization to be calculated as False Acceptance Rate and False Rejection Rate to be calculated based on the FR and NR results. Then, Half Total Error Rate is calculated based on FAR and FRR. HTER value is compared with the reference threshold value. After the comparison, the result will be provided as real or fake. If the Half Total Error Rate is less than threshold value then it is real image. Otherwise that image is fake image.

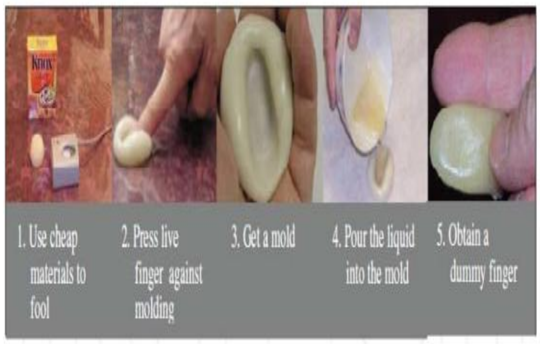

Fig 2: Fake fingerprint Creation

The fake finger has been created easily by intruders and fake finger creation is shown in Fig 2. There is much more difference between real image and fake image. The 27 Image Quality Assessment is used for identify the quality of the image by various properties. That all Image Quality Assessment techniques are explained as follows:

A. Full Reference

The gray scale image I is filtered with low pass Gaussian filter in order to generate the smoothed version I'. The low pass Gaussian filter value σ is 0.5. Then, the quality between both the images (I and I') is computed according to the corresponding full reference Image Quality Assessment metric. It was having the following types:

1) FR IQMs: Error Sensitivity Measures

This image quality assessment approaches based on measuring the difference (that is, signal difference) between both the distorted and reference images. For clarity, it has been classified into five categories:

- Pixel Difference Measures

This measure is used for compute the pixel wise differences between two images. It include: Mean Square Error (**MSE**) is used for measure the mean squared error between both the images. Peak Signal to Noise Ratio (**PSNR**) is used for measure the maximum possible pixel difference between both the images. The above two MSE and PSNR are the error metrics for compare image compression quality. Signal to Noise Ratio (**SNR**) is used for measure the ratio of useful information to false or irrelevant data in a conversation or exchange. Structural Content (**SC**) is used for identify the structural (blocking) artifact difference between both the images. Maximum Difference (**MD**) is used for measuring the maximum of the error signal difference (color difference) between both the images. Average Difference (**AD**) is used for measuring the average color difference. Normalized Absolute Error (**NAE**) is used for measuring the normalized colour difference between both the images. R-Averaged Maximum Difference (**RAMD**) is used for find the r-highest pixel difference between both the images. Laplacian Mean Square Error (**LMSE**) is used for measure the mean square error in L-shaped domain. This Pixel Difference Measure types are having formulas and that are given below:

$$MSE = (1/NM)\sum_{i=1}^{N}\sum_{j=1}^{M}(a(i,j)-b(i,j))^2$$

$$PSNR = 10\log(\max(a^2)/MSE(a,b))$$

$$SNR = 10\log(\sum_{i=1}^{N}\sum_{j=1}^{M}(a(i,j))^2/(N.M.MSE(a,b)))$$

$$SC = 10\log(\sum_{i=1}^{N}\sum_{j=1}^{M}(a(i,j))^2/\sum_{i=1}^{N}\sum_{j=1}^{M}(b(i,j))^2$$

$$MD = \max|a(i,j)-b(i,j)|$$

$$AD = (1/NM)\sum_{i=1}^{N}\sum_{j=1}^{M}(a(i,j)-b(i,j))$$

$$NAE = \sum_{i=1}^{N}\sum_{j=1}^{M}|a(i,j)-b(i,j)|/\sum_{i=1}^{N}\sum_{j=1}^{M}|a(i,j)|$$

$$RAMD = (1/R)\sum_{r=1}^{R}\max{}_r|a(i,j)-b(i,j)|$$

$$LMSE = \sum_{i=1}^{N}\sum_{j=1}^{M}(a(i,j)-b(i,j))^2/\sum_{i=1}^{N}\sum_{j=1}^{M}(a(i,j))^2$$

- Correlation Based Measures

The image quality metric is used for find the angle statistics difference between two images. It include: Normalized Cross Correlation is used for checking whether the input image is subset of another image in database or not. Mean Angle Similarity (MAS) which is used for find the scaled difference between two images. For example, both of the image having the same shape. But, the shape is scaled differently. This difference is identified while performing Mean Angle Similarity. Mean Angle Magnitude Similarity (MAMS) is used for identified the difference for size of the object between two images. The above types having formulas that are shown as follows:

$$MAS = 1-(1/NM)\sum_{i=1}^{N}\sum_{j=1}^{M}\mathrm{a(i, j)}$$

$$MAMS = (1/NM)\sum_{i=1}^{N}\sum_{j=1}^{M}(1-[1-a(i,j)][1-(a(i,j)-b(i,j)/255)])$$

- Edge Based Measures

Edges and corners are most informative part of an image which is play important role in the human visual system. It include: Total Edge Difference (TED) is used for find out the edge difference between two images. Total Edge Difference is performed by using Sobel operator. Total Corner Difference (TCD) is used for find out the corner difference between two images. Total Corner Difference is performed by using Harris Corner Detector. This TED and TCD having the following formula:

$$TED = (1/NM)\sum_{i=1}^{N}\sum_{j=1}^{M}|a_E - b_E|$$

$$TCD = (aN_{cr} - bN_{cr})/\max(aN_{cr}, bN_{cr})$$

- Spectral Based Difference

The image quality metric consider the spectral related features. It include: Spectral Magnitude Error (SME) and Spectral Phase Error (SPE). To perform these measures, apply Fourier transform to the input image. Fourier transform is traditional image processing tool for applied to the field of image quality assessment. These types having the following formula:

$$SME = (1/NM)\sum_{i=1}^{N}\sum_{j=1}^{M}(|aF(i,j) - bF(i,j)|)^2$$

$$SPE = (1/NM)\sum_{i=1}^{N}\sum_{j=1}^{M}|\arg(aF(i,j)) - \arg(bF(i,j))|^2$$

- Gradient Based Measures

Gradient conveys important role for visual information used for quality assessment. If the distortions may affect an image, then there is change in its gradient. This metric is used for identify the structural and contrast difference between both the images. These types having following formula:

$$GME = (1/NM)\sum_{i=1}^{N}\sum_{j=1}^{M}(|aF(i,j) - bF(i,j)|)^2$$

$$GPE = (1/NM)\sum_{i=1}^{N}\sum_{j=1}^{M}|\arg(aG(i,j)) - \arg(bG(i,j))|^2$$

2) FRIQM: Structural Similarity Measures

This image quality measure considers the non-structural distortions. It includes: Structural Similarity Index Measure (SSIM) is used for brightness changes between two images and this non-structural should be treated differ from the structural ones. This SSIM considers only the image resolution. Mean Structural Similarity Index Measure (MSSIM) is better indication of image quality than Structural Similarity Index Measure. Weighted Structural Similarity Index Measure (WSSIM) provides efficient result than Structural Similarity Index Measure.

3) FRIQMs: Information Theoretic Measures

This image quality measure is used for identify the mutual information between two images. It Include: Visual Information Fidelity (VIF) is the quality fidelity as the ratio between the total information in the original image and the total information in the distorted image. Reduced Reference Entropy Difference (RRED) does not require the entire image information. It measures the amount of local difference between the original image and the distorted image.

B. No Reference

No Reference Image Quality Measures estimate the quality of an image according to some pre- trained statistical models. It classified into the following types:

- Distortion Specific Approaches

This approach provides the quality score for specific distortion (JPEG, blur, noise, and block). It include: JPEG Quality Index (JQI) used for identify the input image affected by blockiness or not. High Low Frequency Index (HLFI) is used for detect noise and blur in an input image.

- Training Based Approaches

This metric provide the general quality score not related to specific distortion. It include: Blind Image Quality Index (BIQI) having two stages. First stage is classification stage and it checks the probability of each distortion in the image. Second stage evaluates the quality of the image along with each of the distortions. There are some distortions available and they are as follows: JPEG, JPEG 2000 (JP2K), White Noise (WN), Gaussian Blur and Fast Fading (FF). These distortions are found out from the image and final quality score obtained.

- Natural Scene Statistics

This metric use a priori knowledge taken from the natural scene distortion free images for train this NSS model. It extracts the pixel values by using a priori knowledge. The pixel values are compared with the pixels which of the image stored in the database.

IV.RESULTS

In Full Reference, the input image performs Gaussian filtering and Full Reference technique process input image and Gaussian filter input image (apply Gaussian filter to the input image). Gaussian filter has no ringing effect and it is effective than other filter. So, this implementation uses the Gaussian filter.

In Fig 2, that shows the output of original image and Gaussian noise added to the original image. Input image has been selected from the folder by using “Input image” button. The image quality measure values are shown in the other figures. Then, the Gaussian noise added to the original

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image with the range of 0.003 by using "Gaussian Filter" button.

In Fig 3, that shows the output of real image or fake image. The Image Quality Assessment measures (27 measures) were calculated while click the "Measured Value" button. When the "Normalized Value" button was clicked, then the normalized value has been calculated by using 27 Image Quality Assessment measures values. In Fig 4 and Fig 5, that shows the face output.

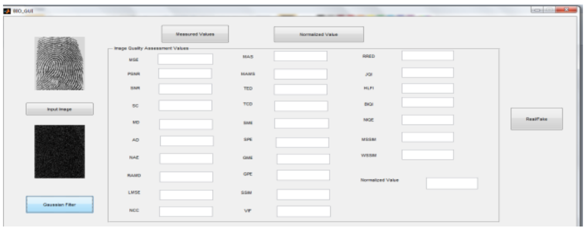

Fig 2: Input image and its Gaussian distortion version for fingerprint

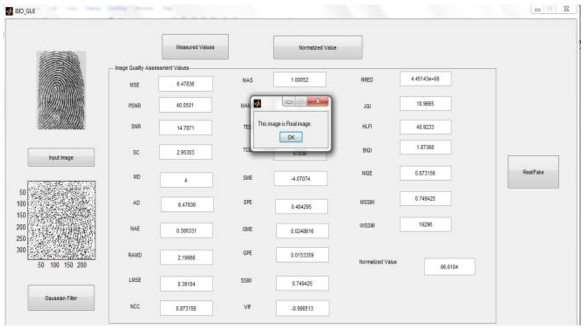

Fig 3: Image Quality Measures are calculated and Result of Real/Fake image for fingerprint

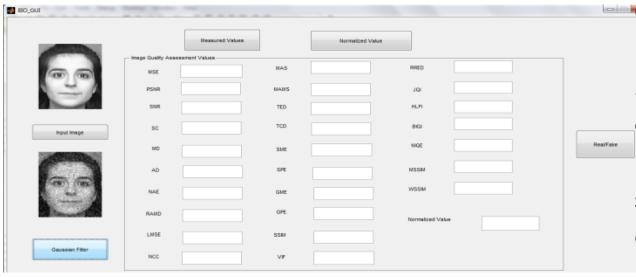

Fig 4: Input image and its Gaussian distortion version for face

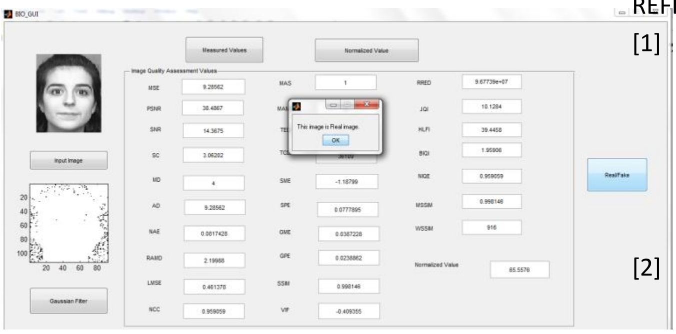

Fig 5: Image Quality Measures are calculated and Result of Real/Fake image for face

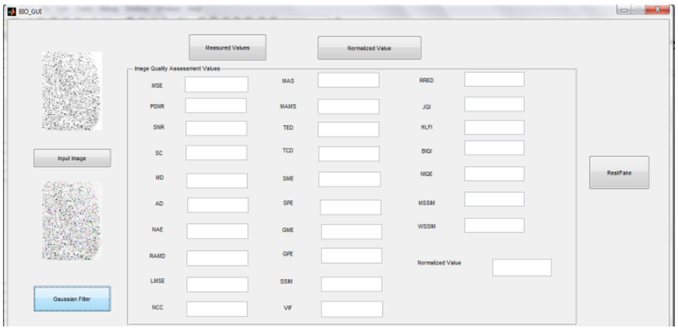

Fig 6: Example: Input image and its Gaussian distortion version for fake fingerprint

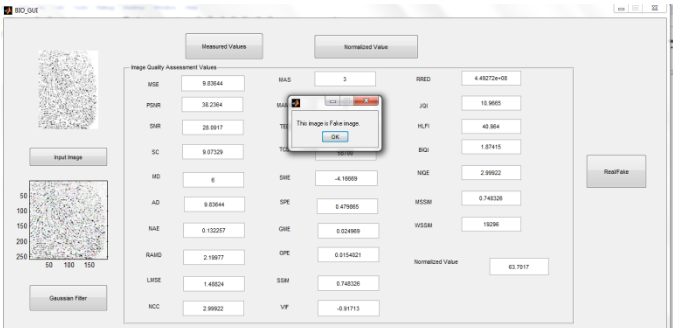

Fig 7: Image Quality Measures are calculated and Result of Real/Fake image for fingerprint

In Fig 6, that shows the fake image and its distorted version. There is more difference between real image values and fake image image values. In Fig 7, that shows the result for fake image.

V.FUTURE WORK

This biometric system to be implemented by using Full Reference and No Reference Image Quality Metric and These Full Reference and No Reference totally having 27 measures. By using this 27 image quality metric can identify the image is real or fake image which is mainly used and applicable in biometric system for avoid intrusion. There are some possibilities for future work. The new image quality measures added with the 27 image quality measures and consider other image based modalities(palmprint, vein).

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